Decision Trees

Nipun Batra and teaching staff

IIT Gandhinagar

July 29, 2025

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Information Gain Intuition

- For examples, we have 9 Yes, 5 No

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- Key insight: Problem is "easier" when there is less disagreement

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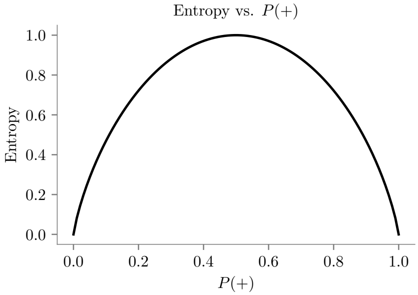
- For examples, we have 9 Yes, 5 No
- Would it be trivial if we had 14 Yes or 14 No?
- Yes!
- Key insight: Problem is "easier" when there is less disagreement
- Need some statistical measure of "disagreement"

Entropy Formula

$$H(X) = -\sum_{i=1}^{k} p(x_i) \log_2 p(x_i)$$

Notebook: entropy.html



Root Node Selection

- Can we use Outlook as the root node?

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Root Node Selection

- Can we use Outlook as the root node?
- When Outlook is overcast, we always Play and thus no "disagreement"

What Does Entropy Measure?

Answer: B) The impurity or "disagreement" in a set of examples - Higher entropy means more mixed classes, lower entropy means more pure subsets.

Entropy Calculation Examples

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Outlook	**Play**
Overcast	Yes
Overcast	Yes
Overcast	Yes
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We have 4 Yes, 0 No
Entropy = 0 (pure subset)

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Outlook	**Play**
Rain	Yes
Rain	Yes
Rain	No
Rain	Yes
Rain	No

We have 3 Yes, 2 No

Entropy = $-\frac{3}{5}\log_2\left(\frac{3}{5}\right) - \frac{2}{5}\log_2\left(\frac{2}{5}\right) = 0.971$

Information Gain Calculations

- Gain($S_{\text{Outlook=Sunny}}$, Temp) $=$ Entropy(2 Yes, 3 No) - (2/5)*Entropy(0 Yes, 2 No) -(2/5)*Entropy(1 Yes, 1 No) - (1/5)*Entropy(1 Yes, 0 No)

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- Gain($S_{\text{Outlook=Sunny}}$, Humidity) = Entropy(2 Yes, 3 No) - (2/5)*Entropy(2 Yes, 0 No) -(3/5)*Entropy(0 Yes, 3 No) $\Longrightarrow$ **maximum possible for the set**

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- Gain($S_{\text{Outlook=Sunny}}$, Windy) $=$ Entropy(2 Yes, 3 No) - (3/5)*Entropy(1 Yes, 2 No) -(2/5)*Entropy(1 Yes, 1 No)

Prediction Example

Prediction for $<$High Humidity, Strong Wind, Sunny Outlook, Hot Temp$>$ is ?

Prediction Example

Prediction for <High Humidity, Strong Wind, Sunny Outlook, Hot Temp> is ?
No

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Apply the same rules, except when depth limit is reached, the leaf node is assigned the most common occurring value in that path.

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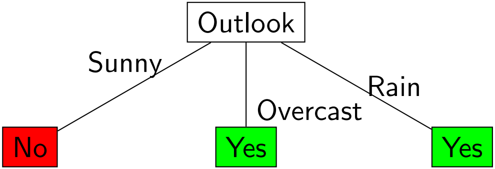

Why Outlook is Good Root?

Answer: B) When Outlook=Overcast, all examples have Play=Yes - This creates a pure subset with entropy=0, maximizing information gain.

Regression Trees

- Any guesses?

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- $\text{MSE Reduction} = \text{MSE}(S) - \sum_v \frac{|S_v|}{|S|}\text{MSE}(S_v)$

Regression Splitting Criterion

Answer: C) Mean Squared Error (MSE) Reduction - For regression, we minimize MSE instead of maximizing information gain.

Continuous Features

Answer: B) Use midpoints between consecutive sorted feature values - This ensures we test all meaningful boundaries between different class regions.

Leaf Node Predictions

Answer: C) The mean of target values in that region - Each leaf predicts the average target value of training samples that reach that leaf.

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- **Solution**: Pruning to control model complexity

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Stop growing tree before it becomes too complex:

- **Maximum depth**: Limit tree depth (e.g., max_depth = 5)

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- **Maximum features**: Consider only subset of features at each split
- **Minimum impurity decrease**: Only split if improvement ¿ threshold

Advantages: Simple, computationally efficient
Disadvantages: May stop too early, miss good splits later

Post-pruning (Tree Simplification)

Grow full tree, then remove unnecessary branches:

- **Algorithm**:

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Systematic approach to find optimal tree size:

- **Cost function**: $R_\alpha(T) = R(T) + \alpha|T|$

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- **Process**:
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  3. At each α, prune branches that increase cost
  4. Select α with best cross-validation performance

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- **Domain knowledge**: Consider interpretability requirements

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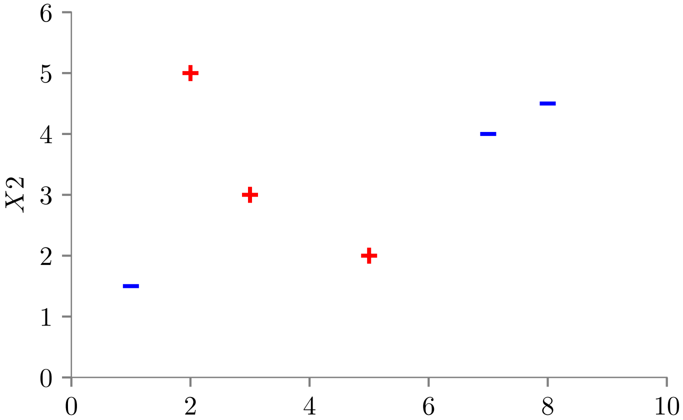
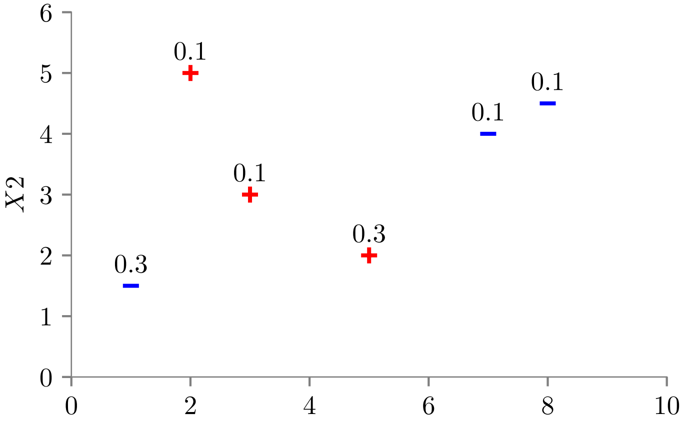
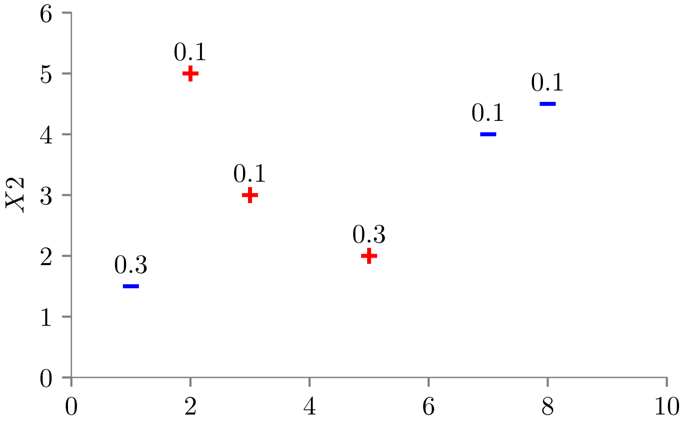
- Issues:
  - Can overfit easily!
  - Empirically not as powerful as other methods

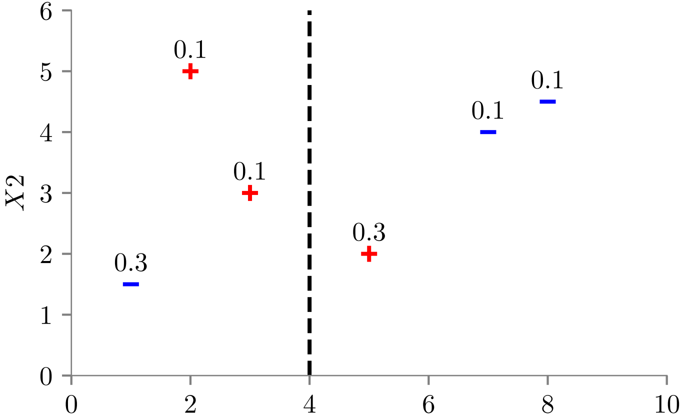

X2
0
1
2
3
4
5
6
0
2
4
6
8
10


6
5
4
3
2
1
0
X2
0
2
4
6
8
10
0.1
0.1
0.3
0.3
0.1
0.1

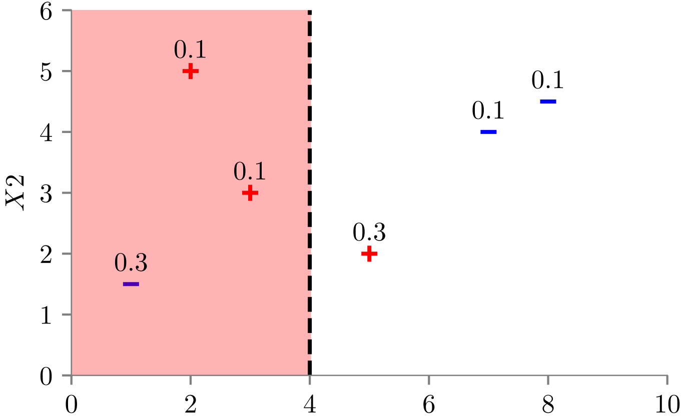


$$\text{Entropy} = -P(+)\log_2 P(+) - P(-)\log_2 P(-)$$

$$P(+) = \frac{0.1 + 0.1 + 0.3}{1} = 0.5, \quad P(-) = \frac{0.3 + 0.1 + 0.1}{1} = 0.5$$



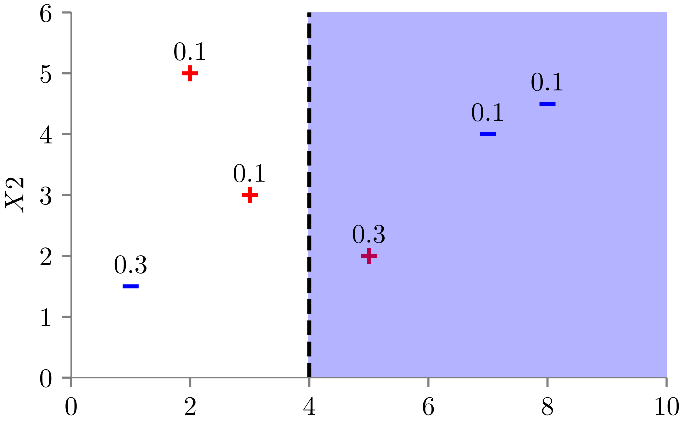
Candidate Line: $X1 = 4(X1^*)$



Entropy of $X1 \leq X1^* = E_{S(X1<X1^*)}$

$$P(+) = \frac{0.1 + 0.1}{0.1 + 0.1 + 0.3} = \frac{2}{5}$$

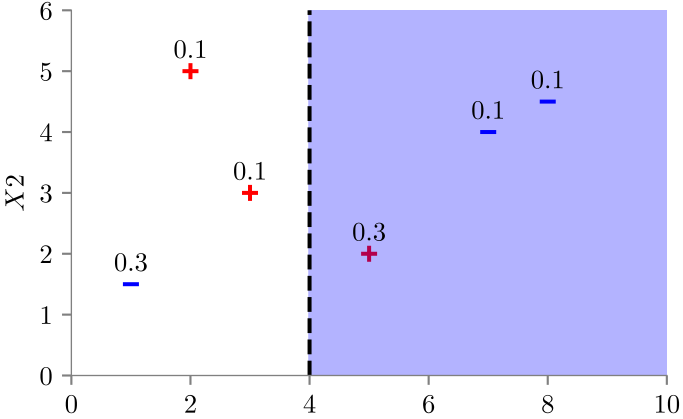
$$P(-) = \frac{3}{5}$$



Entropy of $X_1 > X_1^* = E_{S(X_1 > X_1^*)}$

$$P(+) = \frac{3}{5}$$

$$P(-) = \frac{2}{5}$$



$$\mathrm{IG}(X_1 = X_1^*) = E_S - \frac{0.5}{1} \cdot E_{S(X_1 < X_1^*)} - \frac{0.5}{1} \cdot E_{S(X_1 > X_1^*)}$$